RECLAMATION *Managing Water in the West*

A Distance-Based Methodology for Comparing Longer-Term Performance of Climate Models

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ABSTRACT

In an ongoing regional risk assessment, climate projection distribution functions are being developed for Northern California, representing an ensemble of IPCC AR4 projections produced by 17 coupled models simulating either SRES A2 or B1. It is questioned whether these distribution functions should be built to reflect unequal model-weighting derived from relative model performance in the 20th Century Climate Experiment (20C3M).

To explore this question, 59 20c3m simulations from the same 17 models were evaluated statistically during 1950-99. These statistics were then compared to reference conditions during the same period (NCEP/NCAR Reanalysis, Kaplan Extended SST v2). This comparison was made for a range of statistical metrics applied to different global variables, local variables, and teleconnections relevant to Northern California climate (i.e., local precipitation and surface air temperature, North Pacific sea level pressure index, and Nino3 sea surface temperature index). Metric-specific differences were then aggregated using a distance scheme to reveal multi-metric model-to-reference similarity. Relative model weights were derived from similarity calculations and ultimately used to produce weighted estimates of climate projection distribution functions.

Results show that although bias for a given metric can vary significantly among the models analyzed, the relative degrees of bias varies considerably depending on the variable and/or metric. Consideration of multiple metrics was found to significantly dampen the range of relative model weights. In application, the model weights significantly affected local density aspects of estimated climate projection distribution functions. Their affect on function breadth and central tendency was less significant.

INTRODUCTION

Several methods for generating probability estimates from climate projections have been proposed ([1], [2]). Any method might consider an ensemble of projections representing multiple greenhouse gas emission scenarios simulated one or more times by multiple climate models. In applying these methodologies, it is natural to ask whether all members from a projection ensemble should be valued equally. This latter thought motivates the question explored in this presentation: How does apparent model credibility at a regional scale, translated into relative model weighting, affect the shape and central tendency of regional climate projection density functions?

METHODS

I.a) Philosophy and scope: It is assumed that in the task of projecting 21st century climate, relative model credibility is related to model accuracy in simulating 20th century climate under approximated historical forcings. Following this ideal, a procedure was developed to assess climate model credibility and assign relative model weights based on the relative historical accuracies of the coupled climate models relative to historical climate reconstructions (PART I). Subsequently, a conventional procedure is applied to estimate climate projection distribution functions with and without consideration of these model weights (PART II).

TABLE 1: 21st century models and runs contributing to "credibility analysis" ensemble (part I) and "uncertainty analysis" ensemble (part II).

Ensemble Name (Size) →	UNCERTAINTY (75)		CREDIBILITY (59)
IPCC AR4 Models (17)	**A2 (run #)**	**B1 (run #)**	**20c3m (run #)**
CGCM3.1(T47)	1…5	1…5	1…5
CNRM-CM3	1	1	1
CSIRO-Mk3.0	1	1	1…3
GFDL-CM2.0	1	1	1…3
GFDL-CM2.1	1	1	1…3
GISS-ER	1	1	1…9
INM-CM3.0	1	1	1
IPSL-CM4	1	1	1
MIROC3.2 (hires)		1	1
MIROC3.2 (medres)	1…3	1…3	1…3
ECHAM5/MPI-OM	1…3	1…3	1…3
MRI-CGCM2.3.2	1…5	1…5	1…5
CCSM3	1…5	1…8	1…8
PCM	1…4	2…3	1…4
UKMO-HadCM3	1	1	1…2
UKMO-HadGEM1	1		1…2
ECHO-G	1…3	1…3	1…5

TABLE 2: (Part I) simulated climate variables and statistical metrics relevant to climate in the assessment region of interest (Northern CA, represented by Chico, CA {122W, 40N}). NorCalT and NorCalP denote temperature and precipitation conditions near Chico. NPI equals mean sea level pressure within {30N-65N, 160E-140W}. Nino3 equals mean sea surface temperature within {5S-5N, 150W-90W}. See [5] for metric definitions and computations.

Statistical Metric	Mon. Variable, 1950-99, Global, Local, Teleconnections			
	NorCalT	NorCalP	NPI	Nino3
Long-Term Mean				
Long-Term Variance				
Long-Term Var. Interdec.				
Long-Term Skewness				
Mon. Means: Seas. Amplt.				
Mon. Means: Seas. Phase				
6 yr Sum, 90% Exc				
Annual Max. Mon. 10% Exc				
El Niño Reoccurrence				
Seasonal Corr with **NPI**	(4)	(4)		
Seasonal Corr with **Nino3**	(4)	(4)	(4)	
Annual Corr with **Nino3**				

I.b) Differences between simulation and reference climate metrics: Monthly time series of table 2 variables were extracted from each 20c3m run in table 1 for the latter half of the 20th century (1950-99) and also from reference datasets (for NPI, NorCalP, and NorCalT, the reference data were extracted from the NCEP Reanalysis [3]; for Nino3, the reference data were obtained from the Monthly Atmospheric & SST Indices archive provided by the NWS Climate Prediction Center [4]). Table 2 statistical metrics were then computed from corresponding variable time series, followed by computed difference between simulated and reference metrics (e.g., figures 1-4).

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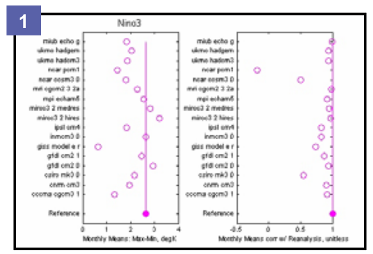

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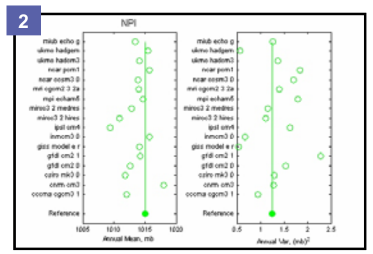

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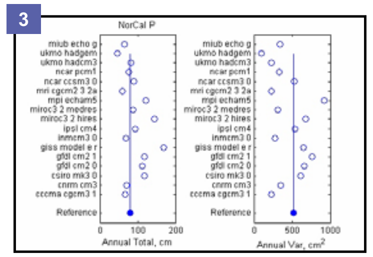

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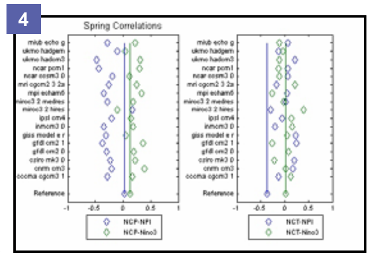

FIGURES 1-4: Simulated and reference 1950-99 statistical metrics for the given climate variable. Two results highlighted: (a) figures 2-4 show that most models tend to underestimate NPI, overestimate NorCalP, and incorrectly simulate sustained winter NPI-NorCalP teleconnection into the spring season; (b) figure 1 reveals that several models poorly capture Nino3 seasonality.

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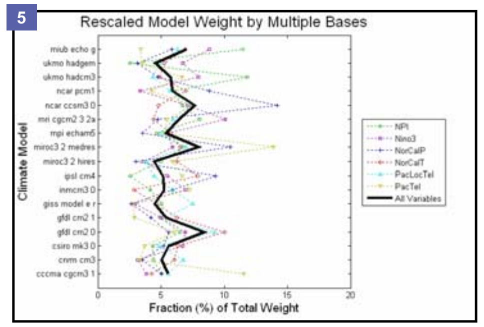

I.c) Translate differences into "similarity distances" and then into relative "model weights": (1) Difference results for model-specific, mulitple-run sets were averaged into single "model-representative" values. (2) The latter were then normalized on a metric-specific basis to have zero mean and unit variance across all model values. (3) The "normalized model-representative differences" were then used to compute model "distance" from reference, "distance" was computed in a "similarity space" defined by "metric dimensions" (e.g., a 7-dimensional space spanned by the 7 NPI performance metrics) using a Euclidean formula. Model weight was then computed as the inverse of this "distance". (4) Finally, the ensemble of model weights were rescaled to sum to one. Steps (3) and (4) were repeated for different "similarity spaces" defined by "all-metrics" of single-variables and "all-variables" (Figure 5) and by all metric subsets of single-variables (e.g., Figures 6-9 for four of the variable categories).

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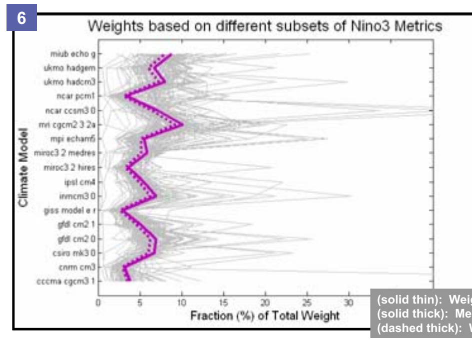

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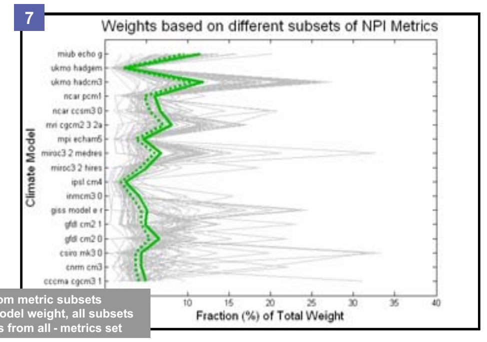

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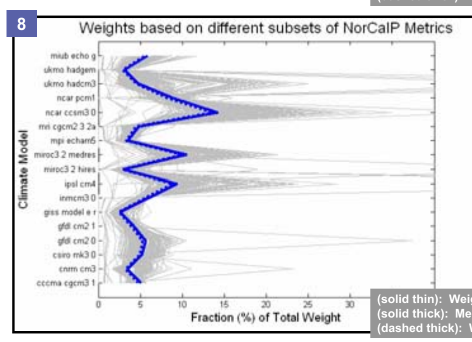

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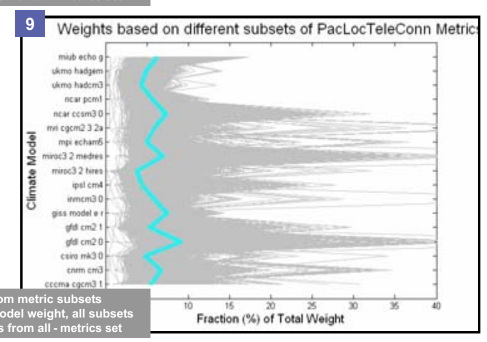

METHODS (Part II) Applying Model Weights to Assess Climate Projection Uncertainty

II.a) Philosophy and overview: Several methodologies have been proposed for developing climate projection distribution functions for single or multi-variable functions ([1], [2]). Although a simplified density estimation procedure is illustrated in this methodology, it would be possible to interchange this procedure with one of the others proposed in literature. There is a common motivation underlying these methods–to consolidate projection information into distributions that help focus planning attention on ensemble consensus rather than extremes ([1]).

Projections are sampled climatologically (figure 10), and resampled proportional to run-representation (table 1) to ensure equal model-weighting. Climatological temperature and precipitation departures from 1950-99 base climatologies are converted into projection distribution functions using kernel density estimation (KDE) techniques (figures 11-16). A second resampling of the projections proporational to model weights is conducted prior to KDE for the "weighted" projection distribution functions.

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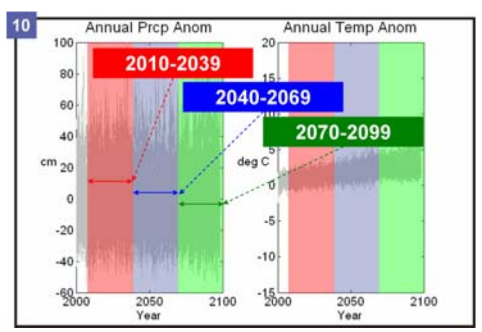

II.b) Comparing the distribution functions: Model weights associated with the figure 5 "All Variables" case are used to produce the weighted functions in figures 11-12 and 14-16. Figure 11 shows weighted and unweighted projection distribution functions (PDFs) for climatological temperature change. Model-weighting seems to affect the local density estimate; however, it has less influence on the PDF shape and central tendency than the breadth of ensemble membership (table 1). Similar conclusions can be drawn from comparison of weighted and unweighted cumulative distributions for temperature change (figure 12), PDFs of temperature change based on the other figure 5 model-weight vectors (figure 13), and from of joint PDFs for precipitation and temperature change (figures 14-16).

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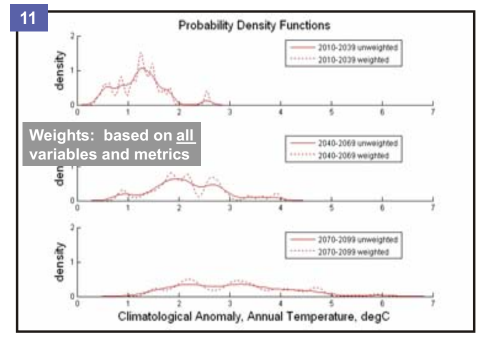

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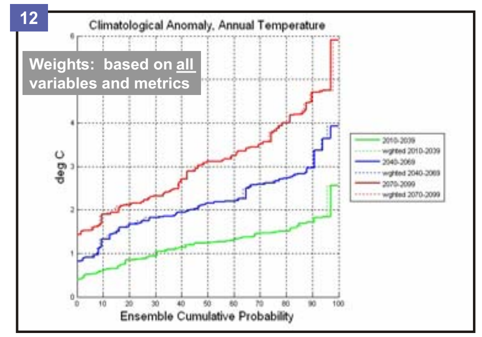

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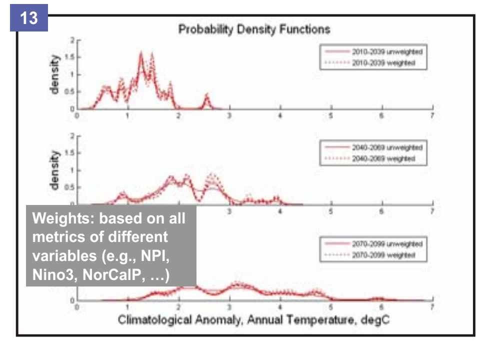

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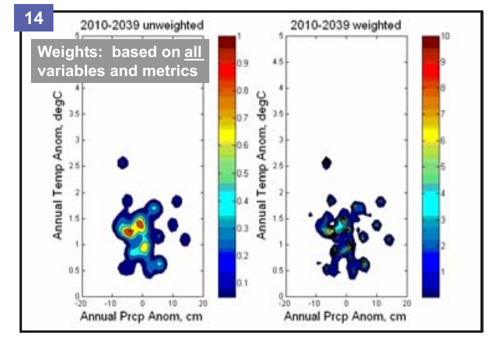

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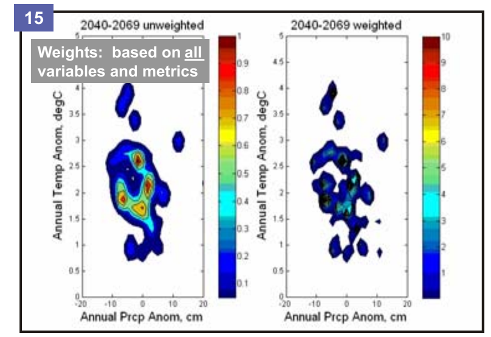

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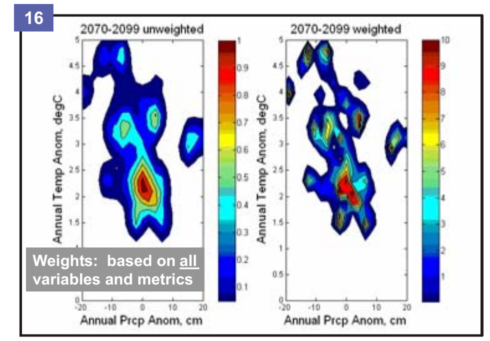

CONCLUSIONS

(Part I) Credibility analysis based on several local and global climate measures allows models to be rated by their historical performances. Constraining the analysis consideration to a more limited set of metrics leads to greater apparent differences between the models. The specific models that rank best, and thus the resulting model weights, depend greatly on the (somewhat arbitrary) choice of metrics.
(Part II) Conditioning the climate projection distribution function by model credibilities affects local aspects of the projection density functions. However, the aggregate function aspects of spread and central tendency tend to be more influenced by the breadth of climate models and climate forcing scenarios represented in the projection ensemble.

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[3] Data obtained from NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at <http://www.cdc.noaa.gov/>.
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